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LONG-TERM UNEMPLOYMENT AND THE GREAT RECESSION: EVIDENCE FROM UK STOCKS AND FLOWS

Carl Singleton*

ABSTRACT

Long-term unemployment more than doubled during the United Kingdom's Great Recession. Only a small fraction of this persistent increase can be accounted for by the changing composition of unemployment across personal and work history characteristics. Through extending a well-known stocks-flows decomposition of labour market fluctuations, the cyclical behaviour of participation flows can account for over two-thirds of the high level of long-term unemployment following the financial crisis, especially the procyclical flow from unemployment to inactivity. The pattern of these flows and their changing composition suggest a general shift in the labour force attachment of the unemployed during the downturn.

I INTRODUCTION

The main aim of this article was to describe how the persistent rise in long-term unemployment (LTU) during the United Kingdom's Great Recession came about (Figure 1).¹ This countercyclical rise in average duration, which typically persists even after unemployment has begun to fall rapidly, has long been of interest to those studying European labour markets.² Renewed international interest has been driven by the significant and less usual rise in US unemployment durations since the 2008–2009 downturn, where LTU rose to its highest post-war level, and persisted even after short-term unemployment had largely subsided.³ Using the Labour Force Survey (LFS), I first discuss how much of the recent UK experience can be accounted for by changes to the composition of the unemployment pool, i.e. by the prevalence of personal

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¹ Throughout this article, and as most commonly defined in the United Kingdom, this refers to those unemployed and looking for work for at least 12 months.

² See for a comprehensive review Machin and Manning (1999).

³ Examples for the US case include: Elsby *et al.* (2011), Kroft *et al.* (2013), Krueger *et al.* (2014) and Kroft *et al.* (2016). A discussion of the features of LTU in several European countries during the Great Recession is provided by a collection of essays in Bentolila and Jansen (2016). Through the case of Spain, Bentolila *et al.* (2017) have assessed the possible role of institutional factors in accounting for the unprecedented rise in LTU in Southern European countries.

and work history characteristics among the unemployed. I then identify which of the flows between employment, inactivity and unemployment durations can account for LTU's rise and persistence.

I find that LTU's rise, from 2007 to its prolonged peak in 2010–2013, cannot be accounted for in any large part by changes in the prevalence of observable characteristics among those looking for work: including the industry and occupation of previous employment, the reasons for leaving a job, and whether an individual was most recently otherwise employed or out of the labour force. This mirrors similar results from Kroft *et al.* (2016) for the United States over the same period.

A notable recent literature has added to earlier work by Clark and Summers (1979) highlighting the cyclical importance of fluidity at the participation margin. Most prominently, Elsby *et al.* (2015) (henceforth referred to as EHS) have demonstrated that a third of historical US unemployment rate variation can be accounted for by the cumulative influence of monthly changes in the transition hazard rates between unemployment and inactivity. Applications of their methodology to flows estimates obtained from the LFS have demonstrated that this result generalises to the United Kingdom, for a period including the Great Recession (Borowczyk-Martins and Lalé, 2016; Razzu and Singleton, 2016). Specifically for long-term unemployment changes, Krueger *et al.* (2014) and Kroft *et al.* (2016) have identified the importance of cyclical patterns in participation flows using calibrated matching models. Both find that allowing for duration dependence in exit rates to employment, as well as

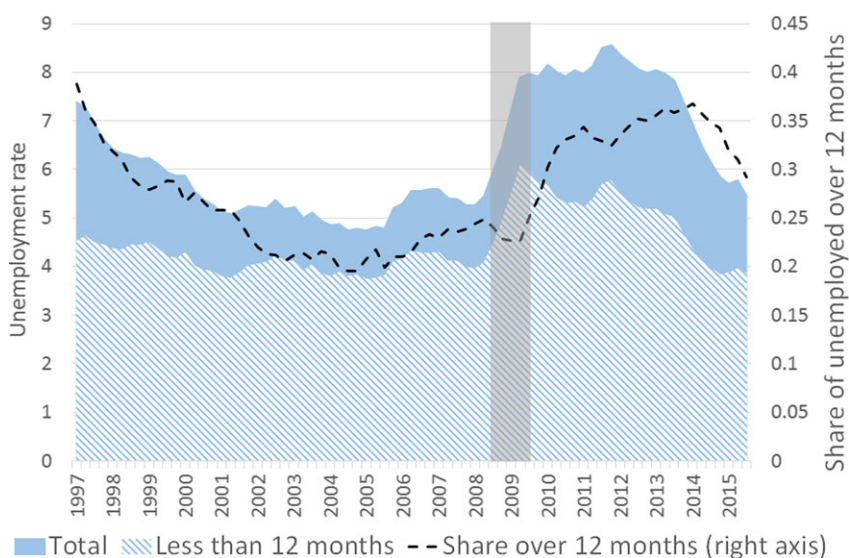


Figure 1. UK unemployment rate and LTU, 1997–2015.

Source: Labour Market Statistics, Office for National Statistics, ages 16–64, accessed November 2015; shaded area denotes UK officially defined recession, 2008q2–2009q2.

[Colour figure can be viewed at wileyonlinelibrary.com]

transitions between inactivity and unemployment, is crucial in matching the rise and level of US LTU post 2008. Instead of similarly calibrating these models to the UK labour market, I explore thoroughly the underlying flows data and how they have determined patterns of LTU over the past two decades.⁴ I do this by extending EHS's stocks-flows decomposition from three to five labour market states: employment, short, medium- and long-term unemployment, and inactivity.

It is not a priori obvious that results for the United Kingdom during the Great Recession will be similar to those found in the aforementioned studies of US LTU. There are notable differences in how OECD countries experienced the Great Recession. The reduction in UK GDP, accounting for pre-recession trends, was roughly twice as great as in the United States by the end of 2011, but the United States nonetheless experienced a greater rise in unemployment (Hoffmann and Lemieux, 2016). The United Kingdom's experience was not only distinct from the United States but also something of an outlier both across countries and compared with past UK recessions. Thus, in the context of what has become the 'The UK Productivity Puzzle' (Barnett *et al.*, 2014; Bryson and Forth, 2015), it would be striking if the determinants of the recent cyclical and persistent level of LTU in the United States and United Kingdom were similar.

To preview the results, aggregate transition rates from unemployment exhibit substantial negative duration dependence.⁵ Flows at the margin between inactivity and unemployment are important in explaining LTU's rise since 2008, and account for as much as half of its variation since 1998. The relative importance of the procyclical unemployment to inactivity flow is especially robust to the alternative methods used here to estimate transition rates. The pattern of how unemployment exit rates account for LTU in the Great Recession is suggestive of shifts in the composition of the unemployment pool, with regard individuals' attachment to the labour force. These exit rates significantly depend on what state individuals entered unemployment from. But more generally, like the stock, the recessionary decrease in transitions from unemployment to inactivity cannot be described by the greater prevalence of characteristics in the unemployment pool that one would expect to be correlated with attachment.

The remainder of the article is arranged as follows. Section II details a counterfactual exercise on whether or not the changing composition of the unemployment pool accounts for the Great Recession's rise in LTU. Section III outlines the methodology used to estimate transition rates, discusses their time series, and briefly gives some detail of the extended EHS stocks-

⁴ As such, this article relates to several others that have used the LFS to characterise the fluidity of the UK labour market, detailing its advantages and limitations in this regard: Gomes (2012), Sutton (2013) and Carrillo-Tudela *et al.* (2016).

⁵ I use the term duration dependence here more loosely than in the specialist literature, which applies this only to the exit probability of individuals. Duration dependence in the United Kingdom has been identified and studied at length previously by among others van den Berg and van Ours (1994).

flows decomposition method. Section IV discusses results using this decomposition, and gives additional focus to the unemployment to inactivity transition rate. Finally, Section V summarises the results and offers some further discussion and implications for future research.

II THE COMPOSITION OF THE UNEMPLOYMENT POOL AND THE LONG-TERM SHARE

Before studying the flows data, I assess the possibility that the changing composition of unemployment could account for LTU over the cycle. This could help to nuance any later flows-based conclusions. For instance, if the rise in LTU was accounted for by a collapse in outflows from unemployment at long durations to inactivity, this could be wrongly attributed to a collapse in individual worker hazard rates, when in truth the composition of the long-term unemployed may have shifted towards those who are more attached to the labour market, such as those who were made redundant instead of having resigned from their last job.

I use the Annual Population Survey (ONS, 2004, 2007, 2010, 2013), restricting attention to the historical UK definition of working-age.⁶ Short-, medium- and long-term unemployment are defined by those who have been unemployed for up to 3, between 3 and 12, and over 12 months, denoted respectively by S , M , and L .⁷ I consider the change in unemployment over three periods: first 2007–2010, i.e. before the Great Recession to the peak rise in LTU, second 2007–2013, to assess the possibility that composition might have had a greater role during the persistent phase of unemployment, and third 2004–2007, to serve as a baseline. I define types of the unemployed over sex, age groups, region of residence, industry and occupation of the last job, reason for leaving previous employment, type of employment sought, and the time since leaving the last job relative to the length of the current unemployment spell. These types address individuals who have never worked nor had paid employment. Relative to 2004 and 2007, I construct a counterfactual unemployment pool, holding constant the distribution over $\{S, M, L\}$ for each type of the unemployed, but applying the aggregate level of unemployment and its distribution over the different types for 2007, 2010 and 2013. That is, the counterfactual for 2010 only differs from the actual observed unemployment pool in one respect: types are apportioned to $\{S, M, L\}$ according to their 2007 shares thereof.⁸

⁶ Male 16–64, female 16–59. This is also consistent with the age groups for which it is possible to extract a consistent series of gross flows from published Two-Quarter Longitudinal LFS (ONS, 1997–2014) datasets.

⁷ Only these three duration types are considered to be consistent throughout with the set of labour market transition rates that I can reliably estimate from longitudinal survey data later. These particular duration band choices also have the nice result of roughly splitting the unemployment pool evenly, on average, over the period studied, 1997–2014.

⁸ See Online Appendix A for a more detailed description of the data, variables and methodology used in this analysis, as well as full counterfactual results for the baseline 2004–2007 case and long-term shares of unemployment across the various personal characteristics accounted for.

Table 1 demonstrates the results of this analysis between 2007 and 2010/13 (see also Online Appendix Figure A2), showing actual and counterfactual levels of LTU, and changes in the share of those unemployed over 12 months. Each row addresses a single type characteristic in the composition of unemployment, including its interaction with both sex and age group types. The final row interacts more characteristics.

The changing composition of the unemployed was not significant in accounting for the rise in the long-term share of unemployment from around a quarter to a third since 2008.⁹ For example, although LTU's share of unemployment increased 12 percentage points between 2007 and 2013, the change in composition along the reason for leaving a previous job, sex and age groups accounts for only one point. Similarly, other characteristics only account for a small fraction of the increase. In terms of the level of LTU, by 2013 the counterfactuals leave an increase of over 250,000 unaccounted for. Not only is this an observed fact of the initial stage of the downturn to 2010, where we might expect composition to have had a more minor role, but is also the case as LTU persisted through to 2013 and the beginning of the labour market recovery. This is in spite of large pre-recession differences in the likelihood of different types finding themselves in LTU (Online Appendix Table A2). This conforms with the findings of Kroft *et al.* (2016) for the United States over the same period. In addition to the characteristics accounted for by Kroft *et al.*, the length of time since an individual left their last job, relative to the duration of their current unemployment spell, cannot

Table 1

Counterfactual levels and increases in the share of the unemployed who are long-term, 2007–2010/2013

| | Number over 12 months (000s) | | | Increase in share | |
|---|---------------------------------|------|------|-------------------|-----------|
| | 2007 | 2010 | 2013 | 2007–2010 | 2007–2013 |
| Actual | 370 | 740 | 850 | 0.08 | 0.12 |
| <i>Counterfactuals: composition change only</i> | | | | | |
| 1. Region | | 590 | 580 | 0.01 | 0.01 |
| 2. Prev. job industry | | 570 | | 0.01 | |
| 3. Prev. job occupation | | 570 | | 0.01 | |
| 4. Reason left prev. job | | 580 | 580 | 0.01 | 0.01 |
| 5. Type of job sought | | 600 | 580 | 0.02 | 0.01 |
| 6. When left last job | | 580 | 570 | 0.01 | 0.01 |
| Characteristics 1. & 4–6. | | 560 | 590 | 0.00 | 0.01 |

Notes: Counterfactuals give levels and increases in shares for 2010 and 2013 holding constant the distribution over $\{S, M, L\}$ for each stated type of heterogeneity, interacted with sex and age groups, from 2007, and applying the overall distribution of types in the unemployment pool from 2010 or 2013. Source: Author calculations using UK Annual Population Survey, ages 16–64/59, January–December 2007, 2010 and 2013.

⁹ See Online Appendix A for confirmation that this is not an anomalous result for this time period. LTU during more normal times, 2004–2007, is similarly uninfluenced by the composition of those looking for work.

explain a perceptible part of the rise in the LTU share. In other words, changes in the extent to which the unemployed entered form employment or inactivity are not significant.¹⁰ However, this is not to say that the participation margin is not important, only that changing the composition along where individuals enter unemployment from cannot alone explain recessionary LTU.

A concern of this analysis, and how to interpret the results, is that upon conditioning on some observable characteristics, those who are long-term unemployed will become increasingly characterised by something unobservable which tends towards longer spells of unemployment. And given that average durations rise in recessions, dynamic selection of the unemployment pool in this regard will also be cyclical. In spite of this, it remains a surprising result that so little of the change in the distribution of unemployment across $\{S, M, L\}$ can be accounted for by observables. Ahn and Hamilton (2016) have provided a methodology to potentially address the role of unobserved heterogeneity. They conclude that the employment history characteristics of the unemployed are likely to explain more of the rise in average duration than coarser observable information. I have found that this is not the case in so far as employment history can be observed in the LFS. EHS have shown that during recessions, the US unemployment pool does shift towards consisting of those who are more attached to the labour force, such as job losers rather than labour force entrants, and that this is at least a relevant factor in explaining cyclical patterns in exit rates, especially the flow to inactivity. A cautious look at the distribution of personal characteristics across unemployment durations over time, combined with the results of the counterfactual exercise, suggest that recessionary LTU in the United Kingdom is not so discriminating.

III FLOWS DATA AND METHODOLOGY

So far I have shown that changes in the composition of unemployment alone cannot account for recent changes in UK LTU. By identifying the flows and specific transition rates between labour market states which do account for these changes, I can develop a more complete picture of LTU in the Great Recession.

I derive estimates of quarterly gross flows between five labour market states from the Two Quarter Longitudinal LFS datasets, between the fourth quarters of 1997 and 2014.¹¹ The five states are defined as follows: employment, inactivity, short-, medium- and long-term unemployment, denoted by $X \in \{E, N, S, M, L\}$. The LFS has a five wave rotational structure, such that in any

¹⁰ The duration of unemployment in the LFS is derived from the minimum response to when an individual left their last job and the stated length of time looking for work. Where these differ it is implied that an individual has been economically inactive since leaving their last job. In practice this also includes new entrants to the working-age labour force at age 16, who directly become unemployed, though this should be accounted for by age group and never having had paid employment characteristics.

¹¹ These are subsequently seasonally adjusted. See Online Appendix B for adjustment method.

quarter the labour market status of roughly 80% of respondents can be compared with their record from the previous quarter. I use population weights provided by the ONS which address non-response bias in the longitudinal sample. Simple transition rates can be estimated, for example from employment to short-term unemployment, as $\tilde{p}_{ES,t} = \tilde{E}S_t / \tilde{E}_{t-1}$, where $\tilde{E}S_t$ is the gross number of transitions, and where $\tilde{E}_{t-1} = \Sigma_X \tilde{E}X_t$ gives an estimate of the stock in employment.

Employment status classification errors

A major concern when estimating flows by unemployment duration is that the data are potentially rife with classification errors. If labour market status was recorded accurately and conclusively, from one quarter to the next, then zero gross flows from employment to LTU should be observed, or from long- to medium-term unemployment for example. These measured flows in labour force surveys are typically significantly different from zero.¹² This could be explained by the incorrect recollection on the part of respondents regarding the length of time they have been employed or unemployed, or that their own interpretation of their past state is different from the International Labour Organization (ILO) definition assigned to their previous responses. My own reading of the data is that the first explanation is unlikely, as individuals who remain in the same state provide very few duration inconsistencies. There is also no concentration of inconsistent transitions with unemployment durations of 4–5 months. Furthermore, flows between employment and unemployment have relatively few inconsistencies compared with those at the participation margin.

For robustness, I address this empirical phenomenon and consistency concerns in reported transitions in three ways. Actual stocks are obtained from national labour market statistics and are given by the state vector $\mathbf{z}_t = [e, s, m, l]_t'$, with lower case denoting population rates, and where the state space is reduced by noting that the population rates across all five states sum to one. First, I measure transition rates as they are given directly by the data, and make only the standard adjustment that they should support the observed quarterly change in \mathbf{z}_t , abstracting from entry to and exit from the working-age population.¹³ In what follows this is referred to as the ‘naïve’ approach, or specification (I). Second, using the measured rates, I compute the aggregate state-transition matrices for every quarter which are not only consistent with the observed actual changes in stocks but also conform to restrictions that

¹² These gross flows within the US Current Population Survey (CPS), and their cyclical behaviour, are discussed in Elsby *et al.* (2011). Also, the matching model calibrated in Kroft *et al.* (2016) recognises this and allows for empirically observed flows into unemployment at longer durations. See Clarke and Tate (1996) for a thorough analysis of inconsistencies between recorded states and subsequent duration responses in early panels of the LFS.

¹³ See Razzu and Singleton (2016) for a version of the EHS decomposition which does not abstract from working-age entry and exit: the different stocks individuals enter to or exit from can potentially affect the cyclical behaviour of those stocks, though in practice this is negligible.

some of the quarterly transition probabilities ought to have been zero: $p_{EM} = p_{EL} = p_{SL} = p_{LM} = p_{NM} = p_{NL} = 0$. In what follows this is referred to as the ‘restricted’ approach, or specification (II). Third, based on an assumption that the ILO employment status is most likely to have been recorded accurately, some observed transitions are reassigned before computing alternative estimates of the gross flows and transition rates. The latter are then adjusted as per (II) and subsequently referred to as ‘cleaned’, or specification (III).¹⁴

A further concerning source of potential classification errors is not addressed by (III). Using re-interview surveys of the CPS, Abowd and Zellner (1985) found that flows between unemployment and inactivity are the most likely source of these errors in individuals’ longitudinal records. This was also corroborated by Clarke and Tate (1996) within the LFS, who further noted that inconsistencies are greater for groups with characteristics which are likely to be correlated with lower labour market attachment. This latter point is of particular concern when conducting a cyclical analysis of flows, as the composition of the inactive and unemployed pools can be expected to change over the economic cycle, thus leading to correlation between changes in these classification errors and labour market stock measures, potentially biasing any results substantially. EHS suggested a robustness check to demonstrate the direction and potential magnitude of this bias. They referred to this as ‘deNUN-ification’. Monthly transitions between unemployment and inactivity are ignored in what would otherwise have been continuous spells in one state or the other over 4 months. I carry out a similar recoding procedure using up to four consecutive quarters of observations for an individual, but only where it is unambiguous that transitions could not be genuine. For example, an individual who is observed as *NNSN* is not re-assigned to continuous inactivity, whereas individual *NNLN* is. This procedure is carried out subsequent and in addition to the recoding exercise described for (III), and transition rates are again adjusted as per (II). This is referred to in what follows as the ‘deNUN’ approach, or specification (IV).¹⁵ In each specification the adjusted rates are then used to populate a state-transition matrix \mathbf{P}_t . For completeness, a set of continuous time equivalent hazard rates, adjusted to account for potential time aggregation bias, are also estimated using a standard procedure.¹⁶ This is referred to in what follows as specification (V).

Transition rate time series and interpretation

Figure 2 compares the estimated exit rate series from LTU across specifications. The restrictions imposed on the non-naïve specifications imply a significant decrease in the level of exits, to off-set the lack of entries other than from medium-term unemployment. Despite this, the qualitative pattern since

¹⁴ See Online Appendix B for more details of these adjustments, or Borowczyk-Martins and Lalé (2016) and EHS for similar applications.

¹⁵ Online Appendix Tables B1–B3 give details on the extent and effect of the recoding in (III) and (IV) on the measured numbers of gross flows.

¹⁶ See for example Shimer (2012) and also some discussion in Online Appendix B.

the Great Recession remains similar. Specifications (III) and (IV) do not substantially alter the estimated series relative to (II), especially with regard to their cyclical pattern. The level adjustments in estimated transition rates of the ‘restricted’ specifications are somewhat extreme. It is impossible to identify whether the adjustment is mainly driven by incorrect duration records, or an individual having a different interpretation of their previous labour market status as compared with the statistical agency. Adjustments of this kind rely on arbitrary assumptions and only provide a sense of the direction or size of any classification error bias in results. As such, despite some impossible observed transitions, in what follows the naïvely estimated transition rates are mainly studied.

Figure 3 compares the estimated exit rates from specification (I) across unemployment durations, where U more generally denotes unemployment. For p_{UE} , exits to employment decline steeply across all durations in 2008, but although there is some recovery for long-term rates, this is less apparent at shorter durations, where the decline appears to have been more persistent. The levels of these aggregated transition rates suggest negative duration dependence. Further, this appears to reduce during the downturn. This is consistent with the predictions of screening models, where during a downturn the length of an unemployment spell becomes a less informative signal of a worker’s unobservable productivity (Kroft *et al.*, 2013). The estimated levels of transition rates for medium and long-term unemployed to inactivity are close, and their patterns since 2008 are similar. These rates declined in 2008, but remained persistently low thereafter, and began to recover from 2013 onwards. However, the exit rate to inactivity for the short-term unemployed, being over twice as high as at longer durations pre-recession, saw a sharp decrease in 2011, before recovering to its pre-recession level by 2014.

Interpretation of these exit rates is not straightforward. Although the composition of the unemployment pool does not generally explain the rise in

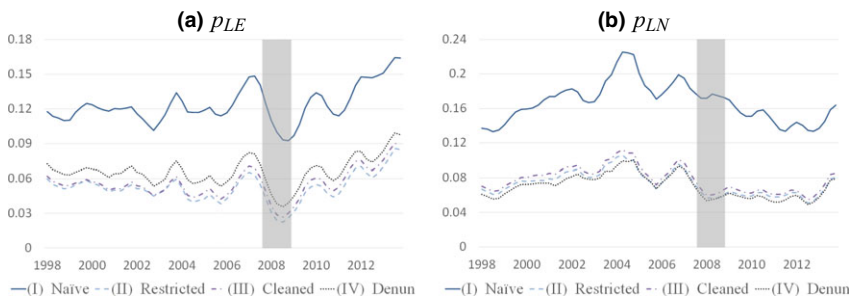


Figure 2. Estimated long-term unemployment exit rates, 1998–2014: comparison of methodologies/specifications.

Source: Author calculations using Two Quarter Labour Force Survey, ages 16–64/59, 1997q2–2015q2, after seasonal adjustment, and with a centred moving average to smooth.

[Colour figure can be viewed at wileyonlinelibrary.com]

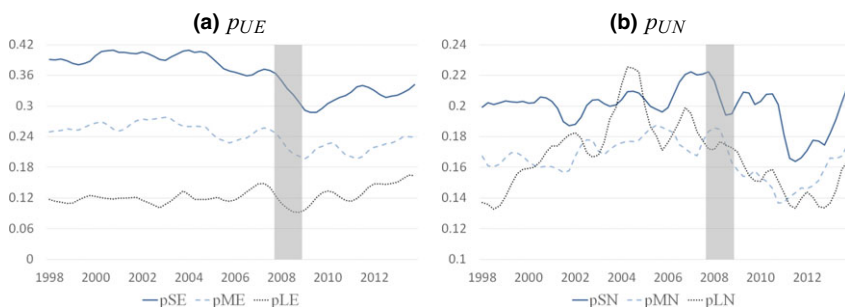


Figure 3. Estimated unemployment exit rates by duration using specification (I), 1998–2014.

Source: Author calculations using Two Quarter Labour Force Survey, ages 16–64/59, 1997q2–2015q2, after seasonal adjustment, and with a centred moving average to smooth the series. [Colour figure can be viewed at wileyonlinelibrary.com]

LTU, this conclusion cannot simply be extended to these exit rates. Besides personal characteristics and employment history changes there is a more obvious composition challenge. Even if the unemployed were identical other than their duration, given the theoretical negative duration dependence of exits, and how $\{S, M, L\}$ are defined, the average rise in durations during a recession would contribute to some of the observed fall in measured transition rates within the grouped duration states.

Decomposition method

I can also derive statistics to assess the relative importance of each transition rate in explaining the change in the observed labour market stocks. The stocks-flows decomposition used here is directly extended to five states from EHS. This method has the advantage over others in so far as it does not rely on an approximation of the labour market to its steady state.¹⁷ Whilst this simplification might be valid for the United States, it is decreasingly so for less fluid labour markets such as the United Kingdom, or for LTU, which could be persistently away from the steady state stocks implied by current estimated transition rates. Relative to other methods used to account for the flows based rise in LTU, such as by Kroft *et al.* (2016), this decomposition approach has one clear advantage. It requires no structure, being a pure mathematical accounting exercise; there is no need to define a matching framework or technology, with some pre-determined structure for any estimated duration dependence in transition rates. There is also a clear disadvantage. The lack of structure limits the possible extent of any counterfactual analysis. It is a further disadvantage that due to small cell sizes in the data, I restrict attention to three broad duration states of unemployment. Thus, I can only account for the partial role of changes in aggregate duration dependence, not being able

¹⁷ See for such examples Solon *et al.* (2009); Shimer (2012); Gomes (2012). For an alternative non-steady state decomposition, using flows estimates from the British Household Panel Survey, see Smith (2011).

to account for any changes which occur within these three unemployment states.

Given the estimated transition rates populating \mathbf{P}_t for each specification, the reduced form of the Markov process governing a five state labour market is given by

$$\underbrace{\begin{bmatrix} e \\ s \\ m \\ l \end{bmatrix}}_{\mathbf{z}_t} = \underbrace{\begin{bmatrix} 1 - \sum_{X \neq E} p_{EX} - p_{NE} & p_{SE} - p_{NE} & p_{ME} - p_{NE} & p_{LE} - p_{NE} \\ p_{ES} - p_{NS} & p_{SS} - p_{NS} & p_{MS} - p_{NS} & p_{LS} - p_{NS} \\ p_{EM} - p_{NM} & 1 - \sum_{X \neq M} p_{SX} - p_{NM} & p_{MM} - p_{NM} & p_{LM} - p_{NM} \\ p_{EL} - p_{NL} & p_{SL} - p_{NL} & 1 - \sum_{M \neq L} p_{MX} - p_{NL} & 1 - \sum_{X \neq L} p_{LX} - p_{NL} \end{bmatrix}}_{\Pi_t} \underbrace{\begin{bmatrix} e \\ s \\ m \\ l \end{bmatrix}}_{\mathbf{z}_{t-1}} + \underbrace{\begin{bmatrix} p_{NE} \\ p_{NS} \\ p_{NM} \\ p_{NL} \end{bmatrix}}_{\boldsymbol{\pi}_t}. \quad (1)$$

I exclude p_{SM} & p_{ML} , as otherwise the variation in these unemployment survival rates could largely obscure the role of entries and exits at shorter durations in the evolution of LTU. However, p_{MM} then still has a somewhat strange interpretation and cannot be trivially excluded. Although the process is memoryless, its effect on long-term unemployment is similar to a decline in exit rates, in so far as it then captures a rise in average duration within M , and the mass of workers here moving closer to L , i.e. then experiencing a p_{ML} transition. The steady-state of (1) is given by

$$\bar{\mathbf{z}}_t = (\mathbf{I} - \Pi_t)^{-1} \boldsymbol{\pi}_t. \quad (2)$$

The change in the labour market state can be re-written as a weighted sum of its lagged value and the change in the present steady state;

$$\Delta \mathbf{z}_t = (\mathbf{I} - \Pi_t) \Delta \bar{\mathbf{z}}_t + (\mathbf{I} - \Pi_t) \Pi_{t-1} (\mathbf{I} - \Pi_{t-1})^{-1} \Delta \mathbf{z}_{t-1}. \quad (3)$$

Iterating (3) back to some initial value of the labour market state, \mathbf{z}_0 , and using a Taylor expansion around each transition rate contained in Π_t , with easily obtained analytical derivatives, the change in labour market state can approximately be written as

$$\Delta \mathbf{z}_t \approx \sum_{ij, ij \notin \{EE, SM, ML, LL, NN\}} \mathbf{c}_{ij,t} + \mathbf{c}_{z_0,t}, \quad (4)$$

where $\mathbf{c}_{ij,t}$ is a vector containing the independent contribution of past and present changes in transition rate p_{ij} to the current change in each labour market state, and $\mathbf{c}_{z_0,t}$ is the contribution of some initial state value.¹⁸ In practice I also distribute the contribution from Δp_{MM} , noting that it ought to be in reality a function of changes in gross flows from between 3 to 9 months

¹⁸ To improve accuracy additional polynomial terms are included in the expansion though cross-derivatives are set to zero.

unemployed to states $\{E, N, S\}$; i.e. for contributions to $\Delta \mathbf{z}_t$ from $\{\Delta p_{ME}, \Delta p_{MN}, \Delta p_{MS}\}_t$ I use

$$\begin{bmatrix} \widehat{\mathbf{c}_{ME}} \\ \widehat{\mathbf{c}_{MN}} \\ \widehat{\mathbf{c}_{MS}} \end{bmatrix}_t = \begin{bmatrix} \mathbf{c}_{ME} + \alpha_{ME} \mathbf{c}_{MM} \\ \mathbf{c}_{MN} + \alpha_{MN} \mathbf{c}_{MM} \\ \mathbf{c}_{MS} + (1 - \alpha_{ME} - \alpha_{MN}) \mathbf{c}_{MM} \end{bmatrix}_t, \quad (5)$$

where values for each α can be estimated using gross flows data from the LFS.¹⁹ As well as being able to study the outcome of this decomposition over specific time periods, a more general measure of each transition rate's importance in determining the change in the stocks can be derived with a variance decomposition. For example, the share of the variance of changes in long-term unemployment explained by its covariance with $\{c_{ES,t}\}_4$ (i.e. the fourth row element of the vector $\mathbf{c}_{ES,t}$; the contribution of past and present changes in p_{ES}) is given by

$$\beta_{ES}^l = \frac{\text{cov}(\Delta l_t, \{c_{ES,t}\}_4)}{\text{var}(\Delta l_t)}. \quad (6)$$

Given (4), the sum of the β^l s for each transition rate contained in Π_t , in addition to the variance shares accounted for by the contribution of the initial labour market state and approximation errors, will necessarily sum to one. Using (4–6) it is straightforward to similarly derive the contributions of transition rates to changes in other labour market variables, such as the overall unemployment population share and its rate of the economically active, by adding rows and linearising. A continuous time equivalent decomposition for use with the estimated hazard rates of specification (V) is a trivial extension of the above.

IV STOCKS-FLOWS DECOMPOSITION RESULTS

I implement the EHS style decomposition described above for quarterly changes between the second quarter of 1998 and the fourth of 2014, with the initial value of the labour market state being the first quarter of 1998.

Variance decomposition

Table 2 gives the complete variance decomposition results for quarterly changes in LTU's population share, and other labour market stocks, for the naïve and restricted specifications of estimated transition rates: i.e. values for the β_{ij} described above. The Online Appendix B contains equivalent results for specifications (III–V), which are viewed as robustness checks. The final rows sum unemployment flow contributions across all durations; i.e. Δp_{EU} gives the contribution from quarterly changes in the aggregate transition rate

¹⁹ For example, the share attributed to the exit rate p_{ME} is estimated as the centred median over nine quarters of $\tilde{\alpha}_{ME,t} = \Delta(\frac{M_{S-9mE}}{M})_t / \Delta \Sigma_{Y \in \{E, N, S\}} (\frac{M_{S-9mY}}{M})_t$. I take the median over a range of t because the series for $\tilde{\alpha}_{ME,t}$ contains outliers which could distort the decomposition, due to the denominator occasionally being very small. I experimented with several ways to make this approximation, but the variance decomposition results were not sensitive to these.

Table 2

Stocks-flows decomposition: 'naïve' and 'restricted' transition rates, 1998q2-2014q4

| | (I)* | | | | (II)† | | | |
|-----------------|-------------------|------------|----------------------------|------------|------------|------------|----------------------------|------------|
| | Δe | Δu | Δu_{rate}^\ddagger | Δl | Δe | Δu | Δu_{rate}^\ddagger | Δl |
| Δp_{ES} | 0.20 [§] | 0.25 | 0.26 | 0.03 | 0.25 | 0.34 | 0.34 | 0.08 |
| Δp_{EM} | 0.06 | 0.08 | 0.08 | 0.01 | | | | |
| Δp_{EL} | 0.00 | 0.02 | 0.02 | 0.06 | | | | |
| Δp_{EN} | 0.16 | 0.00 | 0.00 | 0.00 | 0.16 | 0.01 | 0.01 | 0.01 |
| Δp_{SE} | 0.07 | 0.10 | 0.10 | 0.02 | 0.06 | 0.08 | 0.08 | 0.00 |
| Δp_{SS} | 0.00 | 0.00 | 0.00 | 0.01 | 0.03 | 0.05 | 0.05 | 0.07 |
| Δp_{SL} | 0.00 | 0.00 | 0.00 | 0.04 | | | | |
| Δp_{SN} | 0.00 | 0.08 | 0.07 | 0.01 | -0.01 | 0.06 | 0.05 | 0.00 |
| Δp_{ME} | 0.12 | 0.14 | 0.14 | 0.14 | 0.14 | 0.19 | 0.20 | 0.25 |
| Δp_{MS} | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.09 |
| Δp_{MN} | 0.00 | 0.05 | 0.04 | 0.11 | 0.01 | 0.07 | 0.07 | 0.15 |
| Δp_{LE} | 0.07 | 0.08 | 0.09 | 0.10 | 0.10 | 0.14 | 0.14 | 0.15 |
| Δp_{LS} | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.01 |
| Δp_{LM} | 0.00 | 0.00 | 0.00 | 0.04 | | | | |
| Δp_{LN} | 0.00 | 0.04 | 0.04 | 0.21 | 0.01 | 0.09 | 0.08 | 0.12 |
| Δp_{NE} | 0.30 | 0.01 | 0.03 | 0.00 | 0.32 | 0.00 | 0.03 | 0.00 |
| Δp_{NS} | 0.00 | 0.04 | 0.04 | 0.01 | -0.01 | 0.08 | 0.07 | 0.01 |
| Δp_{NM} | -0.02 | 0.07 | 0.06 | 0.02 | | | | |
| Δp_{NL} | -0.01 | 0.03 | 0.02 | 0.13 | | | | |
| Initial val. | 0.01 | 0.01 | 0.01 | 0.03 | 0.01 | 0.02 | 0.02 | 0.05 |
| Approx. err. | 0.02 | 0.01 | 0.01 | 0.01 | -0.08 | -0.12 | -0.12 | 0.00 |
| Δp_{EU} | 0.27 | 0.36 | 0.36 | 0.10 | 0.25 | 0.34 | 0.34 | 0.08 |
| Δp_{UE} | 0.26 | 0.32 | 0.32 | 0.26 | 0.30 | 0.41 | 0.41 | 0.40 |
| Δp_{UN} | 0.00 | 0.17 | 0.15 | 0.33 | 0.02 | 0.22 | 0.20 | 0.28 |
| Δp_{NU} | -0.03 | 0.14 | 0.12 | 0.16 | -0.01 | 0.08 | 0.07 | 0.01 |
| Δp_{UU} | 0.00 | 0.01 | 0.01 | 0.10 | 0.03 | 0.05 | 0.05 | 0.15 |

'Naïve' transition probabilities, i.e. with no zero value restrictions when adjusting $\tilde{\phi}_t$ (see Online Appendix B). †Transition probabilities adjusted according to restrictions $p_{EM} = p_{EL} = p_{SL} = p_{LM} = p_{NM} = p_{NL} = 0$. ‡ $u_{rate} = u/(u+e)$. §Interpretation: Share of variance in the quarterly change in the employment rate accounted for by past and present quarterly changes in p_{ES} (or hazard rate equivalent), i.e. $\rho_{EU}^ = \frac{cov(\Delta e_t, \{CEU_t\}_1)}{var(\Delta e_t)}$.

Source: Author calculations using Two Quarter Longitudinal Labour Force Survey & Labour Market Statistics, ages 16–64/59.

from employment to all unemployment durations. Initially focusing on the naïve results, Δp_{NL} and Δp_{LN} together explain a third of the variation of changes in LTU. When combined with changes in transition rates between inactivity and other unemployment durations, i.e. Δp_{NU} and Δp_{UN} , this increases to almost a half. This is especially accounted for by the pro-cyclical Δp_{LN} . These same flows changes account for less than a third of total unemployment's fluctuations. Contrasting the cyclical importance of Δp_{UN} with Δp_{UE} , the former is approximately half as important than the latter for total unemployment. This relative difference is however reversed for LTU. Thus, the participation margin appears relatively more important in accounting for the cyclical behaviour of long-term unemployment than the total level.

Comparing results using the estimated restricted transition rates, in terms of accounting for the unemployment rate, the ‘outs’ become more dominant, explaining 60% of the variation in the stock. This is driven by the restriction that all gross flows must enter short-term unemployment. These restrictions do not affect the combined importance of the participation margin, but give more weight to Δp_{UN} . Results for the change in LTU with the restricted set of possible transitions do differ more substantially from the naïve. Instead of explaining almost a half of the variance, transitions between inactivity and unemployment account for less than a third. This difference is mostly explained by a greater relative importance of Δp_{UE} . The importance of Δp_{UN} though remains unchanged.

The additional reassignment of some gross flows data to assess the role of possible classification errors have anticipated effects on the results (Online Appendix Table B4). With regard to the unemployment rate, the effect of using the ‘cleaned’ flows series is to marginally reduce the importance of the participation margin. This is further reduced through ‘de-NUN-ification’. However, through all specifications the pro-cyclical Δp_{UN} (and Δp_{LN}) remains a major factor, explaining a third of the variance in LTU’s changes in the past 16 years to 2015.

As a further robustness check, I compare results using naïve transition rates with those using their time aggregation bias adjusted hazard rate equivalents (Online Appendix Table B5). With regard to the unemployment rate, the share of the variance attributed to changes in the exit rates rises relative to the non-adjusted baseline, from a half to two-thirds, in line with the expected direction of the bias. But addressing this does not alter the principal qualitative result: the participation margin is crucial in accounting for LTU variation.

Focusing on the great recession

Figure 4 plots the cumulative rise in the working-age LTU population share from the final quarter of 2007, and the estimated contributions from past and present changes in the underlying naïve transition rates, using equations (4) and (5). By the beginning of 2012 the population share had reached a peak of 2.5%, more than doubling with an increase of 1.4 percentage points. The majority of the initial rise in 2008 is explained by the pro-cyclical Δp_{UE} . However, this contribution disappears by 2010, and by 2012 changes in the exit rates to employment alone would have implied a lower long-term level than pre-recession, despite the actual level being at its peak. Entries to unemployment from employment contribute a small amount, but this is never substantial. Conversely, by 2010 entries from inactivity can explain almost half a percentage point of the increase, though this subsequently declines to pre-recession levels even as LTU persists. To account for the majority of the persistent and prolonged rise in LTU we must focus on the decline in exit rates to inactivity.

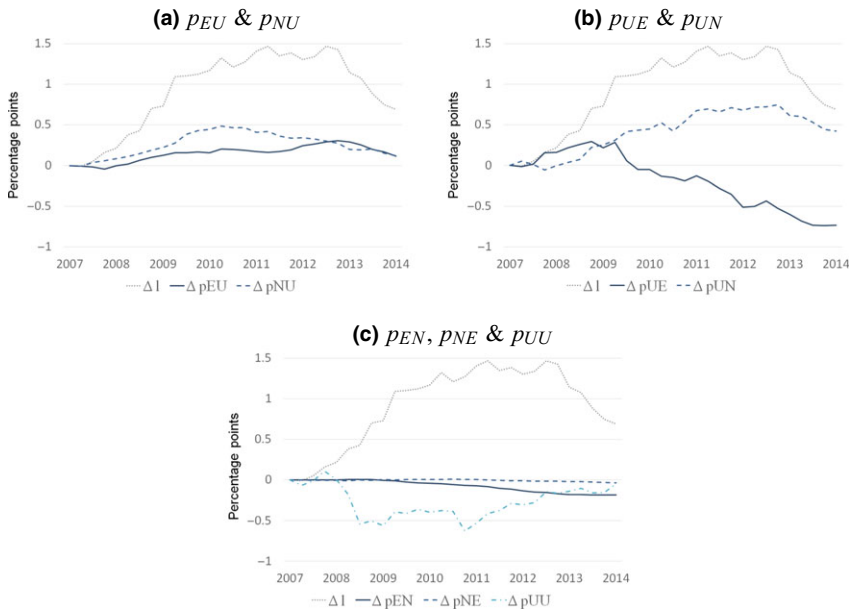


Figure 4. Decomposition of the cumulative change in long-term unemployment, 2008–2014: contributions from individual transition rates.

Notes: Series indexed to zero in 2007q4. Interpretation is the cumulative increase in long-term unemployment's population share since 2007 accounted for by past and present changes in transition rates. Flows contributions may not appear to exactly sum to the change in the stock due to accumulated approximation errors. The initial state value contribution is negligible.

Source: Author calculations using Two Quarter Labour Force Survey & Labour Market Statistics, ages 16–64/59. Transition rates calculated using specification (I). [Colour figure can be viewed at wileyonlinelibrary.com]

These flows patterns, and their contributions to the stock of long-term unemployed, would strongly suggest a compositional change in the unemployment pool. Intuitively, the initial fall in the exit rate to employment affected the already unemployed going into the Great Recession. However, as the downturn persisted, the composition of this pool shifted towards individuals with higher job finding rates. Similarly, these displaced workers are likely to have had a stronger attachment to the labour force, potentially accounting for the procyclical exit rate to inactivity.

Duration dependence or participation flows?

The methodology used here introduces both the limited duration dependence of unemployment exit rates and the role of participation flows in accounting for LTU changes. I can assess the importance of each in turn during the Great Recession. To simplify the problem, for the former I use the restricted transition rate series. With these, which are consistent with actual changes in unemployment, I project forwards the LTU population share as if there was

in fact no duration dependence. That is, given some initial value for LTU, l_0 , I can recursively update the stock as follows,

$$\Delta l_t = \sum_X [x_{t-5} p_{XS,t-4}] \prod_{i=0}^3 (1 - \sum_{X \neq M,L} p_{UX,t-i}) - l_{t-1} \sum_{X \neq M,L} p_{UX,t}, \quad (7)$$

where x is the population rate corresponding to the stock X , and $\sum_{X \neq M,L} p_{UX,t}$ is the total exit rate from unemployment, including restarts. The initial value is chosen as early as possible, 1998q4. Figure 5 compares the actual cumulative rise in LTU, from 2008, with this ‘no duration dependence’ counterfactual. Clearly the limited aggregate duration dependence studied here is not significant in matching the counter-cyclical propagation of LTU, as the two series are almost identical.²⁰

Using the full decomposition results with naïve transition rates, Figure 5 also demonstrates the implied rise in LTU assuming instead no contemporaneous or past changes in transition rates between unemployment and inactivity: i.e. setting Δp_{UN} and Δp_{NU} equal to zero in all periods. This picture simply reinforces results already discussed. Over two-thirds of recessionary LTU is accounted for by changes in flows at the participation margin.

Composition and unemployment to inactivity flows

As previously studied for the stocks above, I can assess the role of composition along some observable characteristics in accounting for these flows

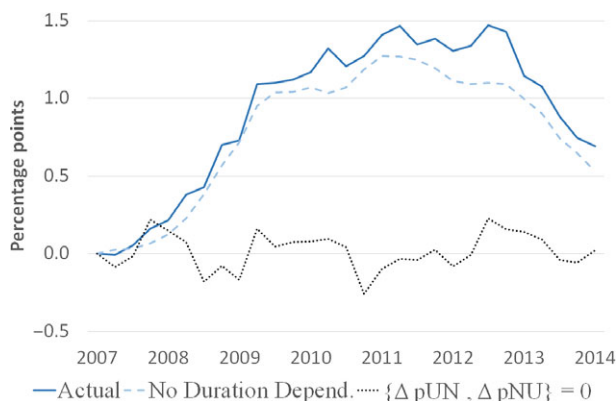


Figure 5. Cumulative long-term unemployment change and two counterfactuals: no duration dependence and no changes in participation flows, 2008–2014.

Notes: Series indexed to zero in 2007q4. Interpretation is the cumulative increase in long-term unemployment.

Source: Author calculations using Two Quarter Labour Force Survey & Labour Market Statistics, ages 16–64/59. [Colour figure can be viewed at wileyonlinelibrary.com]

²⁰ Though as in Kroft *et al.* (2016); Krueger *et al.* (2014) it is highly significant in terms of matching levels of LTU over the whole sample period.

patterns. One distinction of interest is whether individuals entered unemployment from inactivity or employment, as this will correlate strongly with labour force attachment. Although this could to some extent be observed using the five successive waves of the LFS, it can be studied for a larger sample using responses to when an individual left their last job, and whether or not the time since is strictly greater than the derived unemployment duration. Due to sample sizes it would not be robust to disaggregate the long-term unemployed gross flows series further. However, if S and M are combined, it turns out that approximately over the sample period similar numbers in this combined stock entered from employment and inactivity. The level of those unemployed 0–12 months, for whom the time since they left their last job is strictly greater than these grouped duration categories, is denoted by S_n , and for those where this matches, by S_e . For these two new states, as well as $\{E, L, N\}$, I derive seasonally adjusted gross flows and estimated transition rate series, which are adjusted to match observed changes in population rates, as in the naïve specification described before.

Figure 6 shows estimated exit rate series for those unemployed for <12 months, conditional on whether they entered from employment or inactivity. Unsurprisingly, the exit rate to employment is significantly higher for employment entrants, and vice versa, the exit rate to inactivity is higher for inactivity entrants. Pre-recession, p_{S_nN} was over twice as high as p_{S_eN} . Therefore, just through differences in these levels, if the unemployment pool had shifted during the Great Recession towards entrants from employment, this could account for some of the importance of changes in the p_{UN} rate relative to p_{UE} .

Specifically with respect to LTU, and the contribution of changes in exit rates, I can use the gross flows, conditional on point of entry to unemployment, to test the suspicion that my main results are related to composition changes. Figure B1 repeats panel (b) of Figure 4, but overlays the share of

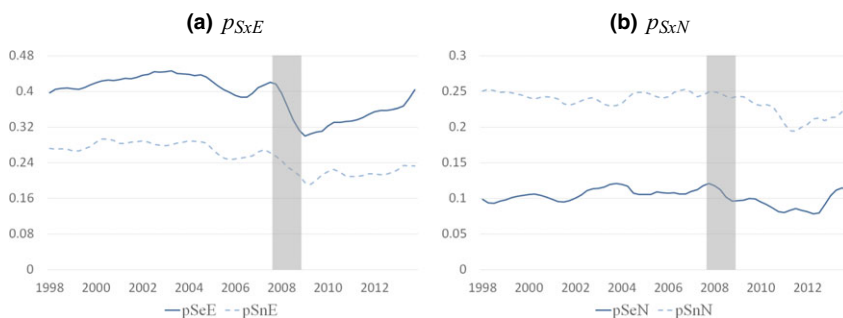


Figure 6. Short-term unemployment exit rates conditional on where entered from, 1998–2014.

Source: Author calculations using Two Quarter Labour Force Survey, ages 16–64/59, 1997q2–2015q2, after seasonal adjustment, and with a centred moving average to smooth. Transition rates adjusted to be consistent with observed changes in stocks. [Colour figure can be viewed at wileyonlinelibrary.com]

gross flows into LTU which were employed prior to becoming unemployed. There is a notable increase in this share by 2009 and onwards, which coincides with the decreasing and increasing contributions of Δp_{UE} and Δp_{UN} respectively. However, we have already seen from the stocks counterfactual exercise that the composition over this particular employment history characteristic does not account for LTU and its persistent rise. The implication being that whilst there is some correlation, much larger shifts in the unemployment pool along these observables would be required to explain the overall rise of the stock and the contributing pattern of the flows.

To see this more generally, I consider whether the changing composition of the unemployment pool can explain the procyclical p_{UN} and p_{LN} transition rates. I derive counterfactual series of these rates that would have occurred had the exit rates of types of unemployed, defined by all possible combinations of some personal and work history characteristics, remained at pre-recession levels, but only the composition of unemployment changed. I estimate these pre-recession exit rates for each type as the arithmetic mean of raw unadjusted quarterly transition rates observed for 2006–2007. I use characteristics and categories considered in the counterfactual exercise in Section II: sex, age groups, type of employment sought, reason for leaving last job, and when the individual left their last job relative to the reported length of the unemployment spell. Figure 7 plots the actual estimated transition rate series along with these counterfactuals. Although the actual unemployment to inactivity transition rate declined steadily from around 0.2 to 0.15 between 2008 and 2011, the counterfactual series only shows a small decline in 2009 and 2010, but thereafter is approximately at pre-recession levels. The long-term to inactivity rate demonstrates a similar pattern. The counterfactual also initially matches the actual series, but cannot then match a greater decrease from 2011

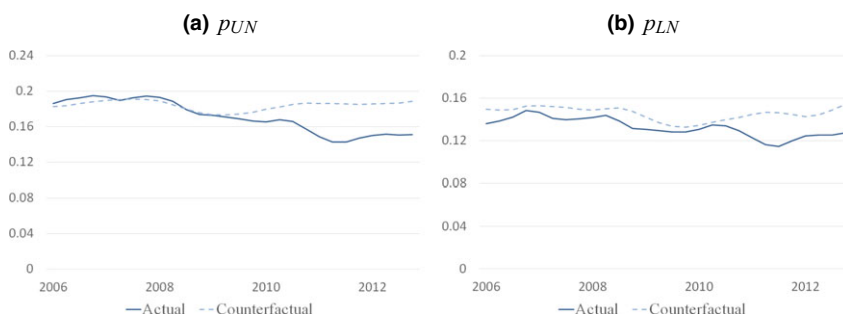


Figure 7. Counterfactual unemployment exit rates to inactivity: changing the composition of unemployment only, 2006–2013.

Notes: Using raw transition rates, not seasonally adjusted but smoothed using centred four quarter moving average. Personal characteristics accounted for in counterfactual: sex, age groups, type of employment sought, reason left previous employment and when left last job relative to length of unemployment spell. See Online Appendix A for details and derived categories of these characteristics.

Source: Author calculations using Two Quarter Labour Force Survey, ages 16–64/59, 1997q2–2015q2. [Colour figure can be viewed at wileyonlinelibrary.com]

onwards. Thus, the changing composition of the unemployment pool across these particular characteristics, which are strongly correlated with labour force attachment in terms of the levels of stocks and flow rates, cannot account for the cyclical importance of unemployment to inactivity flows.

It is possible that changes in UK Government labour market policy during the Great Recession are responsible for some of the results here. However, in Online Appendix C I demonstrate that changes to the eligibility of welfare payments, which could potentially affect flows between active and inactive types, cannot account for the procyclical p_{UN} rate.

V SUMMARY AND FURTHER DISCUSSION

Some observed and derived facts discussed in this article regarding long-term unemployment and the UK labour market during the Great Recession are as follows:

- (1) The changing composition of unemployment, along relevant observable personal and employment history characteristics, cannot account for the significant and persistent rise in LTU since 2008.
- (2) Changes in transition rates between unemployment and inactivity can explain as much as half of the variation in LTU between 1998 and 2014. The flow from unemployment to inactivity's relative importance is robust to various different approaches used to estimate these transition rates.
- (3) Despite (1), the pattern of how changes to flows contributed to the rise in LTU remains consistent with an unemployment pool which shifted towards workers more attached to the labour force.
- (4) Unemployment exit rates exhibit both level and cyclical dependence on whether workers entered from employment or inactivity.
- (5) However, procyclical transition rates from unemployment to inactivity are mostly not accounted for by changes to the observable composition of the unemployment pool.

A significant challenge to the validity of these results remains the longitudinal inconsistencies between states and durations in the LFS. However, it seems a reasonable stance, as others have taken in the literature, to in the first instance take these simply as given, and then for robustness study in what direction any measurement errors would tend to bias results. One way to corroborate them would be using administrative claimant flows data for those receiving out of work payments from government. But at least so far as the United Kingdom is concerned, the available data are typically incomplete, and thus prone to sampling bias, and individuals claiming most major benefits do not fall strictly within ILO employment status definitions.

This article reinforces that the participation margin is likely to be crucial in accounting for the observed amplification of long-term unemployment during recessions, as demonstrated in Krueger *et al.* (2014) and Kroft *et al.* (2016 for the US experience of the Great Recession). An interesting extension of the matching models in these aforementioned studies would be the inclusion of

exit rate dependence on employment history, namely depending on which state workers entered unemployment from. As shown here, this could be significant. The shift of the unemployment pool towards entrants from employment in recessions could potentially off-set a stronger procyclical response and importance of negative duration dependence.

The results of the flows decomposition lead to a strong suspicion that a shift in the composition of the unemployment pool, towards more attached workers, could explain the United Kingdom's rise in LTU. However, the counterfactual analyses of the stock and contributing flows, along some observed characteristics expected to be correlated with attachment, have not shown this. This points towards the likelihood that levels of attachment are challenging to identify from observables. Alvarez *et al.* (2016) have modelled transitions between employment and non-employment and found that unobserved heterogeneity across workers, affecting their degrees of negative duration dependence in exit likelihood, and the resulting dynamic selection of the stocks over time, must play a significant role in accounting for the evolution of the aggregate job finding rate from non-employment. Using a similar model, it would be an interesting direction for future research to consider whether this extends to unemployment to inactivity flows, and how in this way we might account for LTU increases during recessions.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

- Appendix S1.** (a) Composition of the unemployment pool – data and methodology
(b) Labour market flows – data & adjustments
(c) The potential role of labour market policy changes

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